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Observation impact, domain length and parameter estimation in data assimilation for flood forecasting

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ABSTRACT

Accurate inundation forecasting provides vital information about the behaviour of fluvial flood water. Using data assimilation with an Ensemble Transform Kalman Filter we combine forecasts from a numerical hydrodynamic model with synthetic observations of water levels. We show that reinitialising the model with corrected water levels can cause an initialisation shock and demonstrate a simple novel solution. In agreement with others, we find that although assimilation can accurately correct water levels at observation times, the corrected forecast quickly relaxes to the open loop forecast. Our new work shows that the time taken for the forecast to relax to the open loop case depends on domain length; observation impact is longer-lived in a longer domain. We demonstrate that jointly correcting the channel friction parameter as well as water levels greatly improves the forecast. We also show that updating the value of the channel friction parameter can compensate for bias in inflow.

1. Introduction

Data assimilation can improve the accuracy of predictions from flood inundation models by combining forecasts from the model with observations of the system, taking into account uncertainty in both the model predictions and the observations. In this study we use a sequential data assimilation method comprising a forecast-update dynamic feedback loop. During each forecast step, the numerical model runs an inundation simulation. When an observation (or set of observations) is available the simulation is interrupted and the update step is performed; updating combines observational data and model predictions to give a better estimate of the state. The next forecast step then starts, with the adjusted water levels as the initial condition. An update is carried out each time a new observation or set of observations is available.

There are a number of numerical inundation models that can predict the behaviour of flood water given information about the topography of the domain and the amount of water flowing into the area, e.g. HEC-RAS, Telemac, LISFLOOD-FP (HEC-RAS Development Team; Hervouet, 2000; Neal et al., 2012). In a real flood situation, topographical information is often available in the form of a digital terrain model (DTM) and inflow estimates may come from an upstream gauge, or as output from a hydrological model. Observations of the flood may be available from a variety of different sources. These include river depth and flow rate measurements from gauges, and authors have used these data in assimilation schemes, e.g. Mure-Ravaud et al. (2016). However, many catchments are ungauged and the number of gauges worldwide is in decline (Vrsmarty et al., 2001). Observations of flood extent can be obtained from aerial photos, although the cloudy conditions associated with heavy rainfall often limit the usefulness of this information source. Recently, much attention has been paid to the use of synthetic aperture radar (SAR) satellite images in delineating flood extent, since such observing systems have all weather and day and night capability. Water depth information can then be retrieved from SAR satellite images using a high quality DTM as described in Mason et al. (2012) and Brown et al. (2016). Such techniques for extracting information from SAR images are well established, e.g.Thornhill et al. (2012), Mason et al. (2010), Scott et al. (2008) and Scott and Mason (2007).

Various authors e.g. Lai and Monnier (2009), Matgen et al. (2007) and Schumann et al. (2009) have used data assimilation techniques to highlight the fact that although observations from

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SAR can cover a large spatial area, the usefulness of the information they contain is limited in time. Assimilating data from one or more river gauges can help to mitigate this, as shown by Lai and Monnier (2009) and Hostache et al. (2010), but we consider here the situation in which only time-sparse satellite derived water level data is available for assimilation. This leads to a situation in which data assimilation can provide a good analysis - i.e. can correct water levels very well at the time of observations, but the model forecast then moves quickly away from the true water levels during the subsequent forecast step. This short lived improvement in the water levels has been shown in studies such as Andreadis et al. (2007), Neal et al. (2009) and Garcia-Pintado et al. (2013), which use ensemble Kalman Filter data assimilation algorithms, as well as in Matgen et al. (2010), where a particle filter approach is taken. This result indicates that water levels in a river flood situation are not strongly sensitive to initial conditions. In fact, water levels are likely to be more dependent on inflow and model parameter values, and updating one or a combination of these is therefore necessary.

In order to address the short-lived nature of the forecast improvement, authors such as Andreadis et al. (2007), Matgen et al. (2010), Giustarini et al. (2011), Garcia-Pintado et al. (2015), Garcia-Pintado et al. (2013) and Mason et al. (2015) have carried out data assimilation including on-line correction of inflow along with water levels. Inflow correction is shown in all of these studies to give much better forecast accuracy over time than correcting water levels alone. Less attention has been paid to the effect of errors in model parameters in sequential data assimilation, despite the fact that several studies, including Andreadis and Schumann (2014) and the comprehensive review paper by Grimaldi et al. (2016), indicate that model parameters are likely to have an important influence on the behaviour of the flow.

One study in which parameter effects are investigated is Garcia-Pintado et al. (2015), in which water levels, inflows and several model parameter values were updated simultaneously using an ensemble Kalman filter technique. The study used LISFLOOD-FP to model the flooding of the river Severn and tributaries near Tewksbury, UK, in 2014, assimilating real SAR-derived water level observations. A large improvement in forecast skill was seen when inflow was corrected along with water levels, leading to good agreement between the forecast and independently measured gauge data. In this case, channel friction parameter estimation alongside estimation of water levels, inflows and other parameters was not found to improve the forecast significantly, despite the fact that water behaviour is strongly influenced by this parameter. The question of whether the retrieved friction parameter value was correct was left open as the true value for the system was not known.

In this study we address open questions about the role of the channel friction parameter in data assimilation for inundation modelling. We use a similar data assimilation technique to that in Garcia-Pintado et al. (2015) in twin experiments with an idealised topography and an unbiased inflow. This allows us to separate out and further investigate the effect of channel friction retrieval on the forecast. We find that, in contrast with Garcia-Pintado et al. (2015), online estimation of the channel friction parameter along with water levels leads to a large improvement in the forecast skill in our experiments. The twin experiments also show that our data assimilation method is capable of finding an accurate value for the channel friction parameter, even when water depth observations are only available on the flood plain during a flood.

We also investigate the effect of domain length on forecast skill, showing that because the assimilation is able to correct water levels in areas where there are no observations, the time taken for corrected water levels to decay back to the open loop (no assimilation) case is longer for a physically longer domain. Further, we demonstrate that when reinitialising the numerical model after an assimilation, an initialisation shock can occur. We demonstrate an efficient and effective technique for removing this shock, leading to more accurate forecasts in the hours immediately following an assimilation.

This paper is organised as follows: In section 2 the numerical inundation model is described, the data assimilation method is outlined and our novel re-initialisation method is demonstrated. In section 3 the experimental configurations for various simulations are described. Section 4 shows the effect of including online channel friction parameter estimation along with water level estimation, and compares results from different length domains. Section 5 draws conclusions about the effects of domain length and channel friction parameter estimation.

2. Methodology

In this section we describe the methods used in this study. In section 2.1 the numerical inundation model is outlined. Section 2.2 contains information about the data assimilation method used. In section 2.3 we discuss the impact of assuming the water has only hydrostatic momentum at the start of a forecast step and describe our approach to dealing with problems caused by this assumption.

2.1. Numerical inundation model

In this study we use a numerical flood model we have developed using Clawpack (Clawpack Development Team, 2014; Mandli et al., 2016; LeVeque, 2002), an open source collection of FORTRAN and python code that can be used to solve a wide variety of conservation laws. Clawpack uses finite volume methods and sophisticated Riemann solvers to treat systems of partial differential equations; in this work the equations of interest are the 2D shallow water equations that describe how river and flood water will move in space and time. The model splits the domain of interest into N cells and calculates the water depth in each cell. The code is capable of dealing with shocks in the solution, such as bores that may occur following a sudden increase of inflow into a particular river stretch. Clawpack deals effectively with the wet-dry interfaces which are present in an inundation event, and preserves depth non-negativity (George, 2008).

The shallow water equations for two spatial dimensions, x and y, can be written as (e.g. LeVeque (2002))

$$\frac{\partial \mathbf{q}}{\partial t} + \frac{\partial \mathbf{F}(\mathbf{q})}{\partial x} + \frac{\partial \mathbf{G}(\mathbf{q})}{\partial y} = \mathbf{R}(\mathbf{q}), \tag{1}$$

where $\mathbf{R(q)}$ is a source term and $\mathbf{q}$ is a vector of conserved quantities

$$\mathbf{q} = \begin{bmatrix} h \\ hu \\ hv \end{bmatrix}, \tag{2}$$

h represents depth of the fluid, and u and v represent velocity in the x and y directions respectively.

In equation (1), $\mathbf{F(q)}$ and $\mathbf{G(q)}$ represent fluxes of the conserved quantities in the x and y directions respectively. For the shallow water equations these are